



## Underwater acoustic imaging: sparse models and implementation issues

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# Underwater acoustic imaging: physically-motivated sparse models and validation on real data

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CIRM, Marseille, France

Supports:  
ANR ASAP



# Outline

Problem statement

From synthetic to real data imaging

New sparse models and model validation

Conclusion

# Outline

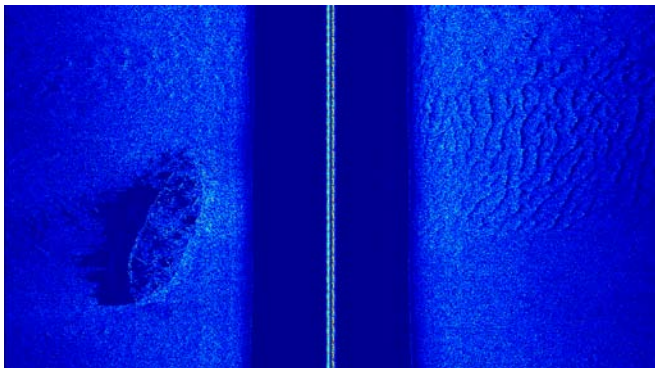
Problem statement

From synthetic to real data imaging

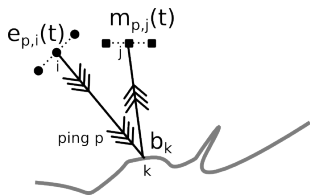
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# Underwater acoustic imaging (UWA)



# Underwater acoustic imaging: direct problem



- ▶ Successive emission sequences, or *pings*, indexed by  $p$ .
- ▶  $e_{p,i}$ : emission at emitter  $i$ , ping  $p$ .
- ▶  $m_{p,j}$ : measurement at receiver  $j$ , ping  $p$ .
- ▶  $b_k$ : backscattering coefficient at position  $k$ .
- ▶  $\tau_{ik} + \tau_{kj}$ : propagation delay.

Direct problem:

$$\forall p, j, t, m_{p,j}(t) = \sum_k b_k \sum_i e_{p,i}(t - \tau_{ik} - \tau_{kj})$$

In a matrix form,

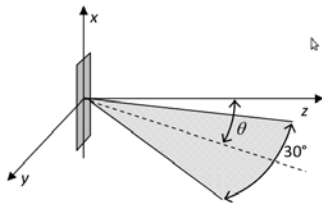
$$\mathbf{m} = \Phi \mathbf{b}$$

# Underwater acoustic imaging (inverse) problem

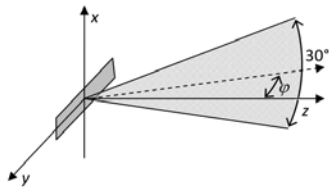
$$\mathbf{m} = \Phi \mathbf{b}$$

Goal: estimate vector  $\mathbf{b}$  from measurement vector  $\mathbf{m}$  and known matrix  $\Phi$  (made with delayed versions of the emitted signals).

# Classical approach to sonar: beamforming (BF)



Beam at emission ( $E(\theta)$ )



Beam at reception ( $R(\phi)$ )

In a nutshell:

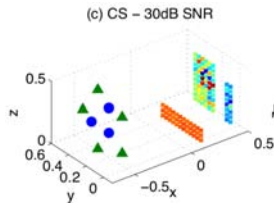
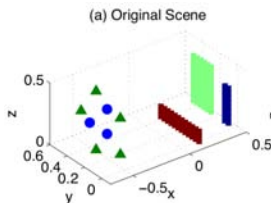
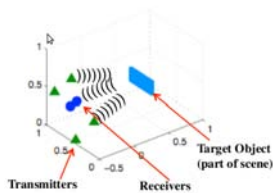
- ▶ A beam = focus on a quasi-planar region ( $\theta$  or  $\phi$ ).
- ▶ Forming E or R beams = apply gains/delays to transducers.
- ▶  $E(\theta)$  beam  $\cap$   $R(\phi)$  beam = image point in direction  $(\theta, \phi)$ .
- ▶ Successive pings = successive beams with varying angles.
- ▶ BF imaging = linear estimator  $\hat{\mathbf{b}}^{\text{BF}} \triangleq \mathbf{W}\mathbf{m}$  for some  $\mathbf{W}$ .

**Limit.:** resolution (primary lobe), artifacts (sidelobes), not 3D imaging.



# Sparse approaches to sonar: state of the art

Physically-motivated sparsity: most of the points in the 3D space are not scatterers (air, water).



$$\begin{cases} \mathbf{m} = \Phi \mathbf{b} \\ \mathbf{b} \text{ sparse} \end{cases} \Rightarrow \hat{\mathbf{b}}^{\text{CS}} = \arg \min_{\mathbf{b}} \|\mathbf{b}\|_1 + \mu \|\mathbf{m} - \Phi \mathbf{b}\|_2^2$$

From:



P. Boufounos, Compressed sensing for over-the-air ultrasound, ICASSP 2011.

But: tests are on simple synthetic data.

# Our focus

- ▶ Challenges when moving from synthetic to real data.
- ▶ New sparse model, validity of the sparse models on real data.

# Outline

Problem statement

From synthetic to real data imaging

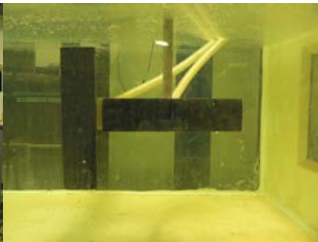
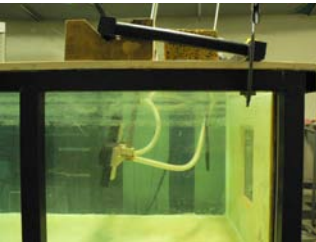
New sparse models and model validation

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# From tic to real data: challenges

## Processing real data implies:

- ▶ Handling a 3D grid with a higher number of points;
- ▶ Detecting targets that are not located on the grid points;
- ▶ Detecting complex-shape objects rather than a simple pattern like a square;
- ▶ Using non-ideal transducers with directivity patterns and calibration issues;
- ▶ Handling phase issues: propagation, modulation by a carrier frequency;
- ▶ Processing noisy measurements.



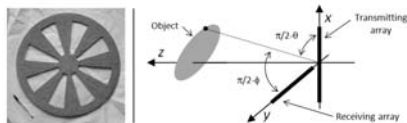
# Experimental features

## General settings

- ▶ 64 emission channels
- ▶ 64 reception channels
- ▶ 128 transducers (E or R each) along 2 26cm line arrays
- ▶ Carrier frequency: 480 kHz
- ▶ Bandwidth: 160 kHz
- ▶ Sampling @ 2 MHz

## Current choices

- ▶ One 64-E line array
- ▶ One 64-R line array
- ▶  $\mathbf{e}_{i,p} \triangleq \delta_{i,p} \mathbf{e}$
- ▶  $\mathbf{e}$ : pure sine+truncated Gauss envelope (10 periods)
- ▶ Target:  $\varnothing 52\text{cm}$  wheel, plywood+sand, 1m away.



# Discretization & dimensionality issues

Full tank discretized with step  $\lambda$ :  $K = 48 \cdot 10^6$  voxels in the grid.  
Measurement length:  $13 \cdot 10^6$  samples.

## Problem size

$$\begin{array}{ccc} \begin{bmatrix} \mathbf{m} \end{bmatrix} & = & \begin{bmatrix} \Phi \end{bmatrix} \begin{bmatrix} \mathbf{b} \end{bmatrix} \\ \in \mathbb{C}^{13 \cdot 10^6} & & \in \mathbb{C}^{13 \cdot 10^6 \times 48 \cdot 10^6} \quad \in \mathbb{C}^{48 \cdot 10^6} \end{array}$$

Size reduction:  $\Phi \in \mathbb{C}^{13 \cdot 10^6 \times 48 \cdot 10^6} \rightarrow \Phi \in \mathbb{C}^{1,327,104 \times 70,272}$

# OMP: naive $\rightarrow$ efficient implementation

## OMP implementation

*Residue initialization:*  $\mathbf{r} \leftarrow \mathbf{m}$ ;

*Sparse support initialization:*  $\Omega \leftarrow \emptyset$ ;

**for**  $K = 1$  to  $K_{\max}$  **do**

*Atom selection:*  $\hat{k} \leftarrow \arg \max_k |\langle \mathbf{a}_k, \mathbf{r} \rangle|$

$O(N_T N_R N_P \times K) \rightarrow O(N_T \log N_e + N_R N_P K)$

*Sparse support update:*  $\Omega \leftarrow \Omega \cup \{\hat{k}\}$

*Sparse representation update:*  $\hat{\mathbf{b}}_{\Omega} \leftarrow \Phi_{\Omega}^+ \mathbf{m}$  (adaptive update)

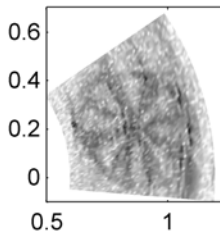
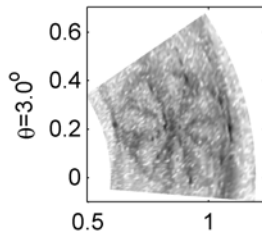
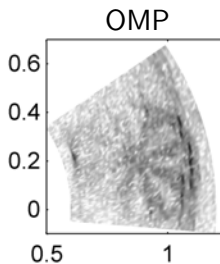
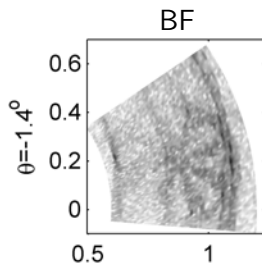
*Residue update:*  $\mathbf{r} \leftarrow \mathbf{m} - \Phi_{\Omega} \hat{\mathbf{b}}_{\Omega}$

**end for**

*Output:*  $\hat{\mathbf{b}}^{\text{OMP}} \leftarrow \hat{\mathbf{b}}_{\Omega}$ .



# Results



Stefanakis et al.,  
*Sparse Underwater  
Acoustic Imaging:  
A Case Study,*  
ICASSP 2012.

# Outline

Problem statement

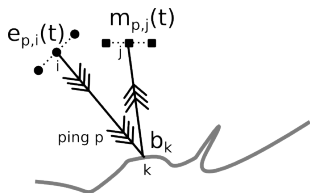
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# Directional scattering model: principle

In the standard (omnidirectional) scattering model,  $b_k$  depends on position  $k$  only:

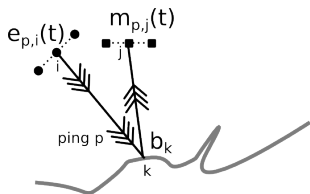


$$m_{p,j}(t) = \sum_k b_k \sum_i e_{p,i}(t - \tau_{ik} - \tau_{kj})$$

New directional scattering model:  $b_{ikj}$  depends on the incoming direction from emitter  $i$  and outgoing direction to receiver  $j$ ,

$$m_{p,j}(t) = \sum_k \sum_i b_{ikj} e_{p,i}(t - \tau_{ik} - \tau_{kj})$$

# Directional scattering model: physically-motivated

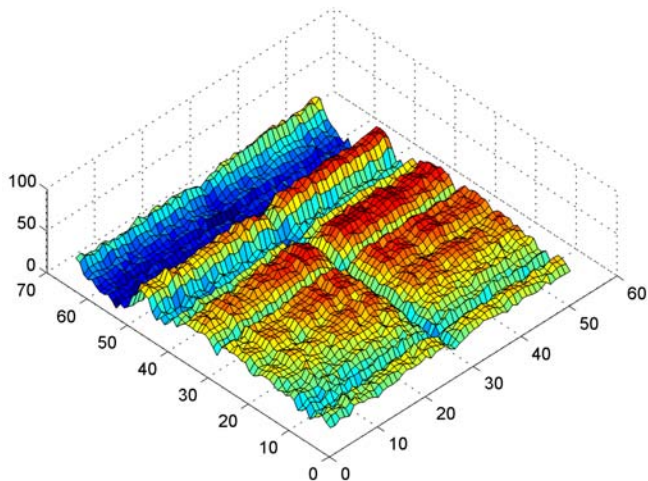


$$m_{p,j}(t) = \sum_k \sum_i b_{ikj} e_{p,i}(t - \tau_{ik} - \tau_{kj})$$

Motivations:

- ▶ scatterers are not omnidirectional
- ▶ transducers may not be calibrated:  $b_{ikj} = \gamma_i b_k \gamma_j$

# Directional scattering model: validation



# Directional scattering model as a sparse model

$$m_{p,j}(t) = \sum_k \sum_i b_{ikj} e_{p,i}(t - \tau_{ik} - \tau_{kj})$$

Sparsity in the omnidirectional scattering model:  $\forall k \in \Omega^c, b_k = 0$

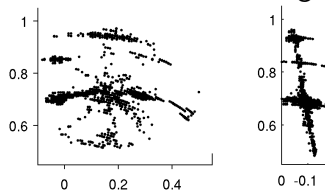
Sparsity in the directional scattering model:  $\forall k \in \Omega^c, \forall i, j, b_{ikj} = 0$

The resulting model is a mixture of:

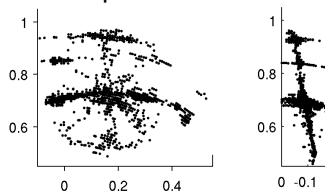
- ▶ a *joint sparse model* (Duarte et al., 2005)  
due to the dependance on receiver  $j$
- ▶ a kind of *harmonic sparse model* (Gribonval and Bacry, 2003)  
due to the dependance on emitter  $i$

## Fresh results...

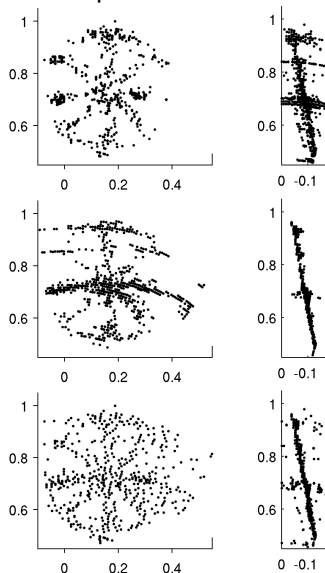
Calibrated beamforming



Calibrated omnidirectional sparse model



Variant of the directional sparse models



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# Conclusion

- ▶ Proposed physically-motivated sparse models
- ▶ Designed tractable algorithms
- ▶ Designed a new device
- ▶ Got new measurements
- ▶ Obtained promising results

## Many perspectives

- ▶ New models: attenuation/propagation, transducer calibration, directivity
- ▶ New settings: antenna random geometry, random sequences
- ▶ Fast algorithms
- ▶ Performance assessment

Thanks!



N. Stefanakis, J. Marchal, V. Emiya, N. Bertin, R. Gribonval, P. Cervenka, *Sparse Underwater Acoustic Imaging: A Case Study*, submitted to ICASSP 2012.



*New papers in preparation*